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Flexible operation of post-combustion solvent-based carbon capture for coal-fired power plants using multi-model predictive control: a simulation study

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Abstract— Solvent-based post-combustion CO_2 capture plant has to be operated in a flexible manner because of its high energy consumption and the frequent load variation of upstream power plants. Such a flexible operation brings out two objectives for the control system: i) the system should be able to change the CO_2 capture rate quickly and smoothly in a wide operating range; ii) the system should effectively remove the disturbances from power plant flue gas. To achieve these goals, this paper proposed a multi-model predictive control (MMPC) strategy for solvent-based post-combustion CO_2 capture plant. Firstly, local models of the CO_2 capture plant at different operating points are identified through subspace identification method. Nonlinearity analysis of the plant is then performed and according to the results, suitable local models are selected, on which the multi-model predictive controller is designed. To enhance the flue gas disturbance rejection property of the CO_2 capture plant and attain a better adaption to the power plant load variation, the flue gas flow rate is considered in the local model identification as an additional measured disturbance, thus the predictive controller can calculate the optimal control input even in the case of flue gas flow rate variation. Simulation results on an MEA-based CO_2 capture plant developed on gCCS show the effectiveness and advantages of the proposed MMPC controller over wide range capture rate variation and power plant flue gas variation.

Keywords: Post combustion CO_2 capture; Power Plant; Flexible Operation; Multi-model predictive control; Nonlinearity analysis; System Identification

I. INTRODUCTION

1.1 Background

With the increasing concern on global warming and its potential effect on climate, ecology and environment, CO_2 emission

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reduction has been regarded as a key step in the international community to alleviate these issues[1]. As the main power generation devices, coal-fired power plants (CFPPs) are the largest stationary emission source of CO_2 worldwide [2]. For this reason, while extensively promoting the renewable energy and making effort to improve the efficiency of conventional CFPPs, CO_2 capture from CFPPs has been recognized as the most effective and direct way to achieve a large-scale CO_2 emission reduction in the future 30 years [3].

Among various CO_2 capture technologies, solvent-based post-combustion CO_2 capture (PCC) using MEA solvent proves to be the most promising technology for CO_2 capture in power plants. Because it is well suited for treating flue gas at low CO_2 partial pressure of power plants, and can be easily installed for existing power plants retrofitting. In recent years, many PCC pilot plants have been developed and put into use [4] – [5].

The biggest issue for the operation of solvent-based PCC plant is the high heat consumption used for solvent regeneration. Such heat is generally provided by the steam extracted from the intermediate/low pressure turbine of the power plant, thus results in a significant power reduction of the CFPPs. To this end, many steady-state optimization studies such as equipment and solvent selection [6]-[9], system configuration[10]-[12], parameter settings [8] - [9] have been carried out, trying to improve the efficiency of the capture system. However, in the face of high energy consumption, more and more researchers realize that implementing flexible dynamic operation for CO_2 capture is of great importance to make the technology be widely used in power engineering practice [4], [5], [13]-[20]. During the electricity peak load, the capture system should be able to reduce its capture rate rapidly to avoid the high cost of energy. On the other hand, when there is tight restriction on CO_2 emissions or the carbon price is higher, the capture system could increase its capture rate quickly [21].

Another big issue, which has critical impact on the operation of the PCC system is from the integrated CFPPs. In the context of growing electric power demand, the magnitude of the cyclic variation of the grid load is increased, and the extensive use of renewable sources such as solar, wind and hydro power are severely influenced by the season and the weather condition, thus, CFPPs have to participate in the grid power regulation frequently and quickly in a wide range nowadays [22]. As a result, the flue gas flow rate of CFPPs will follow the load variation and change rapidly, which brings in strong disturbances to the capture plant [5]. Therefore, to achieve a wide range application, the PCC plants are forced to have a flexible adaption to the flue gas flow rate variation of upstream CFPPs.

1.2 Motivation

To overcome the aforementioned issues and to attain a flexible operation of PCC system, a well-designed control system is required to ensure the correct operation of the entire process, i.e. to follow the capture rate demand rapidly and smoothly in a wide range and to alleviate the influences of flue gas variation effectively.

Currently, most of the control studies of the PCC system are still stayed in the conventional PI/PID control stage [4], [5], [15],

[16], [23]-[26] . Such a design has been proved for its value for regulation and disturbance rejection during normal operation around a given capture rate, however, it may not meet the design specifications for a high level flexible operation of PCC process, the reasons are: i) The CO_2 capture system is a multi-input multi-output (MIMO) system, while the PI/PID control systems are designed based on separate single-input, single-output (SISO) loops, thus the interactions among different variables and properties cannot be taken into account; ii) Due to the slow dynamics of chemical reaction and heat transfer, the PCC system has a typical large inertial behavior [5], while the control action of PI/PID controllers can only be made in the presence of deviation. This control manner may not meet the quick regulation need of the PCC system; iii) in general, the parameters of the PI/PID controllers are set at a given load condition. Therefore, when the flue gas flow rate of the upstream CFPP varies or the capture system changes its capture rate in a wide range, the operation performance of the PCC system is degraded because the dynamics at other operating points may become different.

Recently, model predictive control (MPC) [27], which uses a process model to predict the future response of the plant and calculate the optimal future control sequence has been employed in the PCC system control [13], [14], [17], [18], [28]-[34]. Since MPC is naturally suited for multi-variable and large inertial system control, better performance has been shown compared with the conventional PI/PID controls. For most of the MPC designs in the CO_2 capture system, a linear model developed around a given operating point is used for the prediction [13], [17], [18], [29], [30], [33], [34], such a design may not be suited for a wide range capture rate variation because it is impossible for the linear model to approximate the global nonlinear dynamics. The resulting model mismatch will cause a severe control performance degradation or even unstable of the closed-loop system. To this end, a few scholars proposed to use nonlinear model predictive control (NMPC) [14], [28], [31], [32]. However, it is hard to develop a satisfactory nonlinear model with high accuracy and good structure easy for advanced control design. Moreover the nonlinear optimization during the implementation of the NMPC is weak in robustness and time consuming.

On the other hand, the validations of the control systems in the case of upstream flue gas flow rate variation have been made in some studies. To our best knowledge, it still has not been studied regarding how to actively deal with its impact in the control design stage. Therefore, in spite of the effectiveness of MPCs in tracking the desired capture rate, it cannot remove or alleviate the flue gas disturbances rapidly.

These shortcomings motivate us to investigate the nonlinearity distribution of the solvent-based PCC system and to design a multi-model predictive control (MMPC) system using the combination of several local linear models and predictive controllers. The flue gas flow rate is considered as a measured disturbance in the developed model, so that correct model prediction can be made even in the presence of flue gas flow rate variation. The resulting MMPC system is expected to have a satisfactory capture rate tracking performance and flue gas disturbances rejection performance, and to provide a powerful method towards the flexible operation of the PCC system.

1.3 Literature Review

The earliest studies of solvent-based PCC process were focused on the steady state optimization. A steady state plant model was first developed and simulated under various conditions such as different solvent concentrations, operating parameters and configurations, better choices which can provide a lower cost for the capture system can then be found through comparisons [6]-[12].

The steady state model is impossible to represent the dynamics of this process, thus cannot provide enough information for control design. For this reason, much attention has been paid to the dynamic modelling of the solvent-based PCC system . In the first stage, models for standalone absorber and stripper were developed, the behavior of these columns was then tested through dynamic simulations. For example, Lawal and et al [35] built a dynamic absorber model using both the equilibrium and rate-based approach, and the dynamic simulation showed that the ratio between lean solvent flow rate and flue gas flow rate is critical to maintain the performance of absorber. Ziaii and et al [36] developed a model for the amine regenerative system, dynamic simulation found that lean solvent loading has key influence on the reboiler temperature. Nevertheless, analysis of the stand-alone columns is insufficient to thoroughly understand the dynamics of the integrated PCC process since there exists a strong coupling between two linked columns. To this end, many efforts have been made to develop detailed first principle models for the PCC system using various simulation software such as gPROMS [4], [5], Aspen Dynamics [15], [16], Modelica [37], Matlab [38] and gCCS [39], [40]. Numerous simulations are then performed and the transient influences of flue gas flow rate/composition, rich/lean solvent flow rate and reboiler heat duty on CO_2 capture rate and thermal energy consumption are fully investigated. These studies clearly showed that the influence of lean solvent flow rate and reboiler heat duty on the capture rate has big time constant, while the variation of flue gas flow rate will change the capture rate very quickly, moreover, there are strong couplings among key loops of the capture system. In many of these studies, it was also pointed out that the capture system is highly nonlinear [41], [42]. These investigations provided good guidance for the controller design. As an alternative method to the first-principle modeling, data-driven identification of PCC system has also been studied. In [43], the technique of bootstrap aggregated neural network is used to develop an 8×2 first order model for the PCC system. In [44], NARX models are identified for the absorber, heat exchanger and stripper respectively, these models are then combined according to the physical process to form the integral PCC process model. Although the data-driven model may not be as accurate as the first principle model, it can be easily developed without much knowledge of the process and design specifications. Moreover, the explicit model structure is more convenient and direct for the control design purpose.

Based on the dynamic modelling and process analysis, many studies have been done in the control system development of PCC process. Most of these studies focused on the PI/PID based control loop design. Lawal et al. [4], [5], Lin et al. [15] both proposed a PI based control structure, which used the lean solvent flow rate to control the capture rate and the extracted steam flow rate to control the reboiler temperature. Such a design can attain a quick control of the capture rate even in the presence of flue gas flow rate and CO_2 concentration change. To maintain the hydraulic stability in the absorber and stripper, Lin et al. [16] proposed another structure, which kept the lean solvent flow rate constant and used the lean solvent loading to regulate the CO_2 capture rate. Nittaya et al.[23] investigated the interactions among multi-variables within the PCC system through Relative Gain Array (RGA) analysis. The input-output variables which have the strongest relationship were paired in one control loop. A 6-input 6-output PI control system was then developed centering on manipulating extracted steam flow rate to control the CO_2 capture rate. In [24]-[26], variables which have the closest relationships with the performance of PCC system were selected as controlled variables according to the steady state optimization results, SISO PI control loops were then designed for these variables.

To overcome the SISO PID control's drawbacks in dealing with strong coupling multi-variable system and large inertial behavior, MPCs have been applied in the PCC process to achieve a better flexible control performance. The first attempt was made by Bedelbayev et al [28], who directly used an first principle model based predictive controller for the standalone absorber column. Simulation studies showed that the proposed MPC has a satisfactory performance in case of capture rate tracking and flue gas flow rate variation. In [13], a linear MPC was devised in a double-layer optimal solvent regeneration control system to achieve a fast track of the optimal set-points. In [17], [29]-[32], multivariable MPCs were developed to control the key variables of the integrated PCC process. Owing to the outstanding advantages of MPC in handling strong coupling, large inertial and constraint issues, their results all showed that superior performance can be attained by the MPC compared with the PI/PID based control configurations. In [18] and [33], energy consumptions and CO_2 emissions were considered in the MPC's objective function, and an optimal scheduling sequence of the PCC plant was calculated.

Model is the fundamental and most important element in the MPC design, its accuracy and expression determine the controllers' performance and complexity to a large extent. In most of the mentioned MPC works, a linear model of the PCC system is utilized [13], [17], [18], [29], [30], [33], [34]. However, because the linear model is impossible to approximate the behavior of nonlinear plant, the designed MPC is only suited for a small operating range change. In [14], [28], [31], [32] nonlinear identified or analytical models were directly used for MPC design, however, the nonlinear optimization solving large number of differentia equations lacks of robustness and is time consuming.

1.4 Novel Contributions

To overcome the aforementioned issues, this paper proposes an MMPC for flexible operation of the solvent-based PCC process, the main contributions and novelties of the paper are given as follows:

1) a nonlinearity investigation is made for the solvent-based PCC process using the method of gap-metric;

2) according to the nonlinearity investigation results, an MMPC is designed for a wide range capture rate change of the CO_2

capture plant;

3) the flue gas flow rate is taken into account as a measured disturbance in the MPC design, so that correct model prediction can be made even in the presence of flue gas flow rate variation, and a satisfactory flue gas flow rate disturbance rejection performance can be attained by the proposed MMPC.

The schematic diagram of the proposed MMPC is shown in Fig. 1. Set-point (for carbon capture rate) can be given by the user. Flue gas flowrate changes according to power plants operating load, the signal is utilized in the MMPC design framework to achieve an effective flue gas flowrate disturbance rejection. According to the current CO_2 capture rate, at each sampling time, the local predictive controllers are combined together through the membership function and the calculated global control action is implemented on the capture plant. In essence, this research proposes to use the combination of multiple MPCs designed at different operating points to replace one NMPC for the whole operating range.

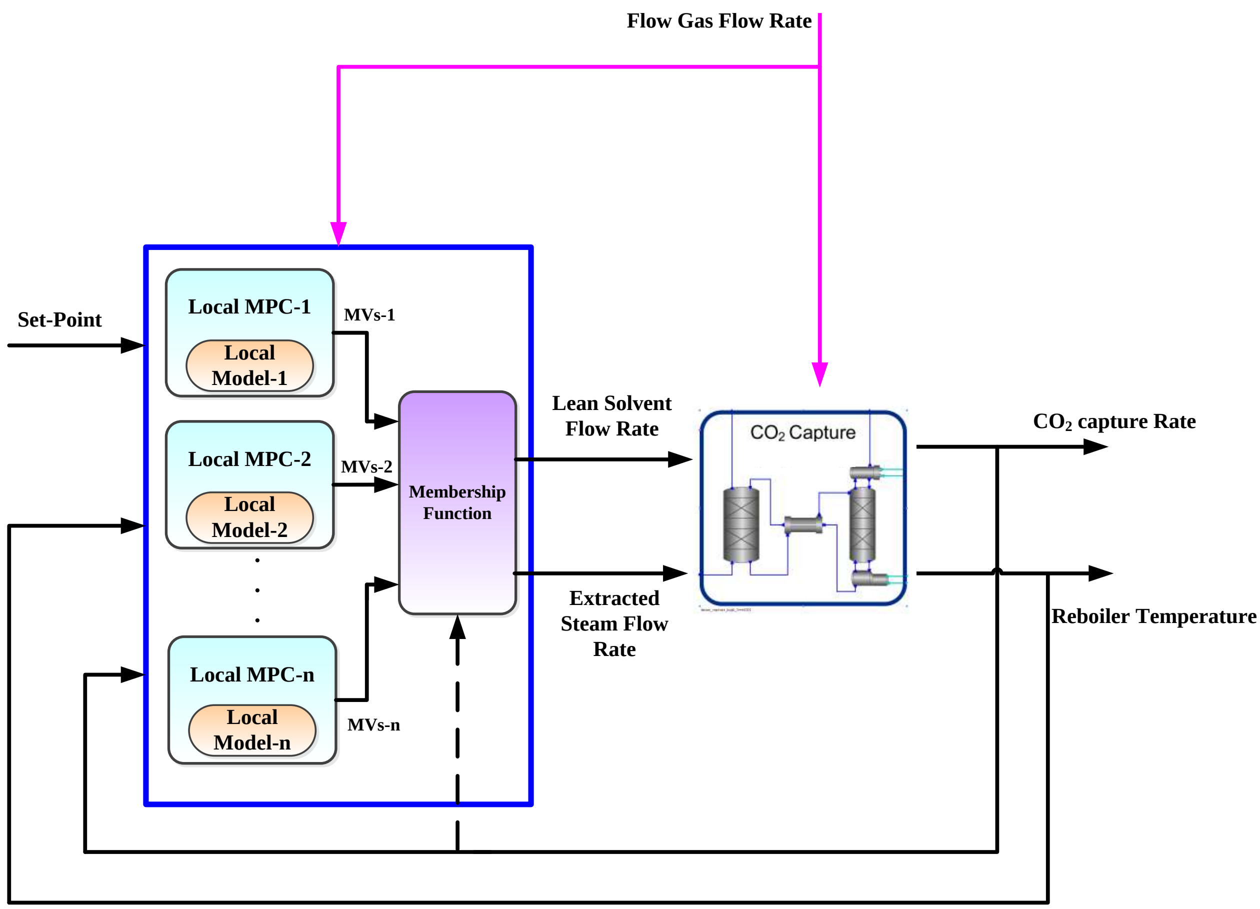

Fig.1 Schematic diagram of the proposed MMPC for the solvent-based post combustion CO_2 capture process

1.5 Outline of the paper

Section I gives the background, motivation and novel contribution of this paper. Section II briefly describes the developed simplified dynamic model for solvent-based carbon capture based on the gCCS (gCCS was developed in gPROMS for power plants, carbon capture, transport and storage by PSE Ltd based in London and is commercially available). The nonlinearity investigation and the MMPC system design is presented in Section III and the validation of the controllers is described in Section IV. Finally, conclusions are drawn in Section V.

II. System Description

A dynamic model of the solvent-based carbon capture plant is developed and used as a simulation platform for control design and validation. The PCC plant under consideration is matched with an 1 MWe coal-fired power plant, which can produce 0.13 kg/s flue gas (CO_2 concentration: 25.2 wt%) at full load condition. 30wt% MEA solvent is used as the sorbent and the specifications of the equipment such as absorber, stripper, reboiler, condenser and cross heat exchanger are selected according to the model developed in [5], which has been validated through operating data of pilot capture plant. To provide a high-fidelity description of the PCC process, the model for these unit operations were developed from the first-principles and then connected based on the working process of CO_2 capture using the gCCS toolkit [39], [40]. The process topology of the PCC model developed in gCCS is presented in Fig. 2.

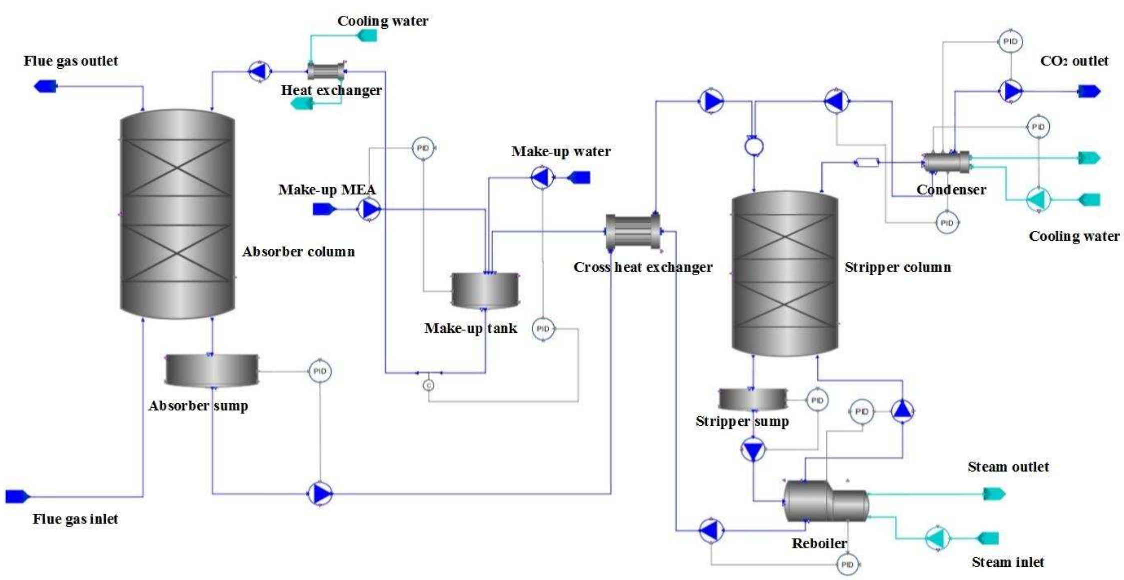

Fig. 2 Schematic diagram of the PCC process as presented in gCCS

For the control system of the PCC process, many variables need to be strictly controlled to guarantee a safe and efficient operation of the plant. Among them, the CO_2 capture rate y_1,

$$y_1 = \frac{CO_2 \text{ in the flue gas} - CO_2 \text{ in the clean gas}}{CO2 \text{ in the flue gas}} \qquad (1),$$

and the reboiler temperature y_2 are two of the most critical variables [4], [5], [15]. The capture rate indicates whether the capture system can fulfill the carbon capture task according to the environmental protection requirements. Reboiler temperature is closely related to the lean solvent loading, which determines the CO_2 absorption ability of the solvent, and an excessively high temperature will cause solvent degradation. For this reason, this paper is focused on controlling these two key variables, the lean solvent flow rate u_1 and turbine extracted steam flow rate u_2 are selected as manipulated variables because they have big influences on the capture rate and reboiler temperature[4], [5], [15]. For other variables such as sump tank level, reboiler/condenser pressure and so on, conventional PI controllers are designed to regulate them within a given operating range.

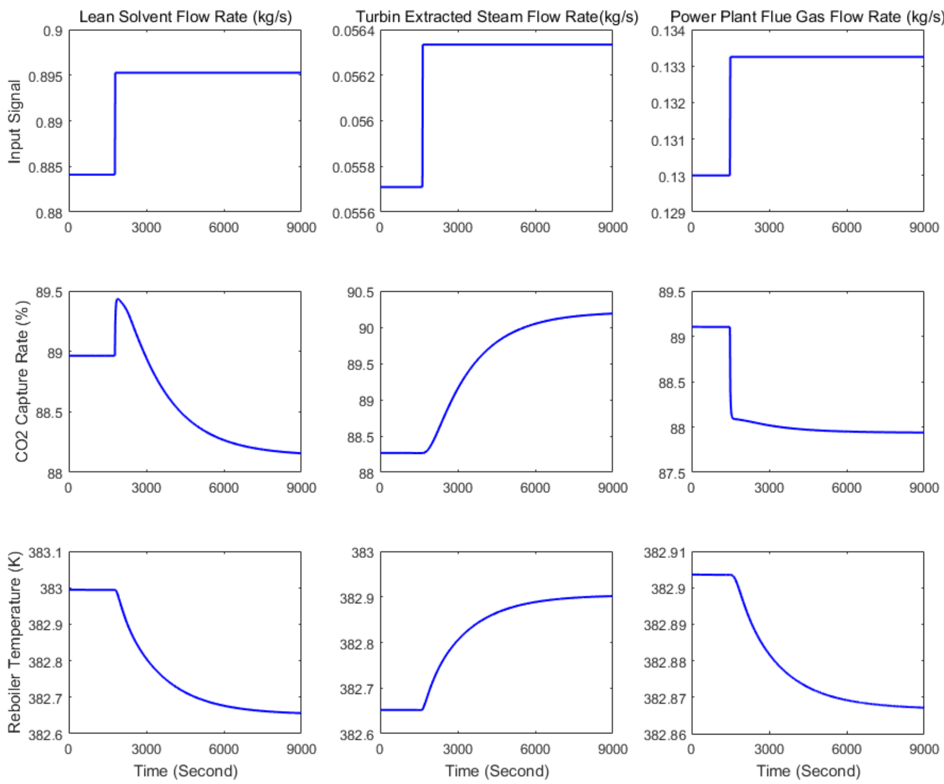

Fig. 3. Responses to three individual step tests for the PCC model developed on gCCS (Left column: step response of lean solvent flow rate u_1; Middle column: step response of turbine extracted steam flow rate u_2; Right column: step response of power plant flue gas flow rate d).

Fig. 3 shows the step response test results around 90% capture rate operating point for the considered variables, which can guide us in the controller design:

1) As indicated in the left column of Fig. 3, an increase of lean solvent flow rate can quickly increase the CO_2 capture rate. However, since the steam supplied to the reboiler does not change, the reboiler temperature will drop and less CO_2 will be stripped off the solvent and the loading of the solvent to the absorber will rise. Therefore, the capture level will drop after a while;

2) As indicated in the middle column of Fig. 3, turbine extracted steam flow rate can change the CO_2 capture rate ultimately. However, its influences on the capture rate and reboiler temperature have large time constants;

3) As indicated in the right column of Fig. 3, the flue gas flow rate will change the CO_2 capture rate immediately because

"the capture rate is defined as (CO_2 in the flue gas − CO_2 in the clean gas)/ CO_2 in the flue gas", it will influence the reboiler temperature slowly and then further change the CO_2 capture rate.

These step response tests showed that the key variables within the PCC process are strongly coupled and has a large inertial behavior, the external flue gas flow rate has a significant impact on the system. Moreover, the wide range flexible operation of the capture process brings severe nonlinearity to the system and higher requirements for the control. Therefore, we propose an MMPC system for the solvent-based PCC process to overcome the weaknesses of the conventional controllers.

III. NONLINEARITY ANALYSIS AND MULTIMODEL PREDICTIVE CONTROL DESIGN

3.1 Nonlinearity Analysis of CO_2 capture system

Under the ordinary MPC design framework, modeling is the first and foremost important step because both the control performance and computational complexity heavily depend on the model's accuracy and structure. For the multi-model control system development, it is important to know the level and distribution of the nonlinearity along the whole operation range so that a minimum number of local linear models can be selected and combined to approximate the nonlinear behavior of the plant. To this end, the nonlinearity of the PCC process along the considered operating range is analyzed first using the approach of gap-metric, which is a measure of the distance between linear models around adjacent operating points [45] - [46].

Because flexible operation of the PCC process requires the control system to be able to change the capture rate quickly in a wide range and meanwhile have a good adaptation to the power plant flue gas flow rate variation, the nonlinearity level along the capture rate side and flue gas side both need to be analyzed.

To investigate the nonlinearity level along the capture rate side, we keep the flue gas flow rate fixed at 0.13kg/s to avoid its influences. The method of subspace identification is then used to identify the local state space linear models around 50%, 60%, 70%, 80%, 90% and 95% capture rate points (the reboiler temperature is kept around 383K during the identification experiment). The gap metric values between the adjacent linear models are calculated and shown in Fig. 4. The gap value is bounded between 0 and 1, and a large value represents a large difference between the two linear models, thus reflects a strong nonlinearity along this range[45] - [46].

For the flue gas side investigation, we keep the CO_2 capture rate within 70%-80% operating range, and identify the local state space linear model at 0.07kg/s,0.10kg/s, 0.13kg/s and 0.15kg/s operating points (the reboiler temperature is kept around 383K during the identification experiment). The gap metric value are calculated as shown in Fig. 5.

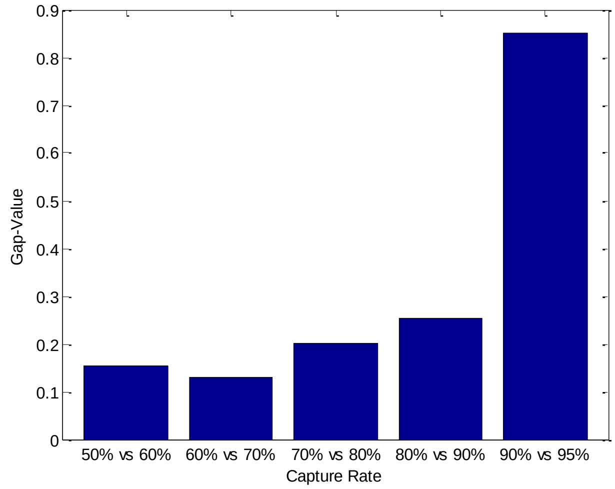

Fig. 4 Gap metric values between adjacent linear models along the CO_2 capture rate side

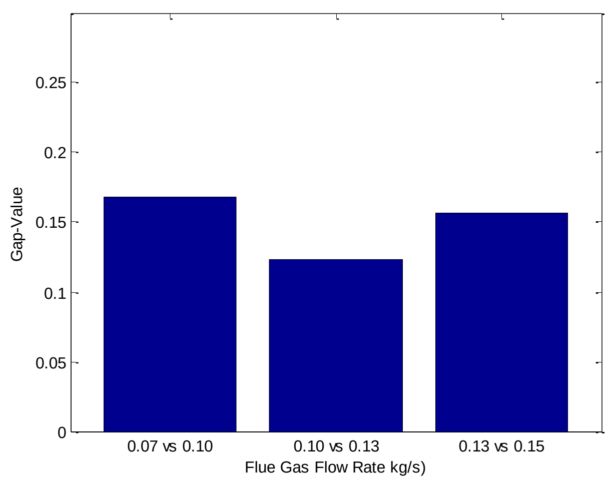

Fig. 5 Gap metric values between adjacent linear models along the flue gas side

Figs. 4 and 5 show that along the CO_2 capture rate side, the level of nonlinearity increases as the capture rate increases, it is weak between 50%-90% operating range, but strong around 95% operating point. On the other hand, along the flue gas side, the level of the nonlinearity is not strong within the range of 0.07-0.15kg/s. Although increasing the number of local model/controllers will enhance the performance of the multi-model control system, it will also increase the complexity of the system structure and the computational effort. Therefore, according to the nonlinearity analysis results, we develop three local models and predictive controllers around 50%, 80% and 95% CO_2 capture rate points to compose the integrated multi-model system, the flue gas flow rate is taken into account in the local model/controller development as an measured disturbance.

3.2 MMPC of PCC process

3.2.1 Local Disturbance Model with Flue Gas Flow Rate Disturbance

Because the flue gas flow rate d can be considered as a measured disturbance, the following state space disturbance model can be used as a local prediction model:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + Ed_k \\ y_k = Cx_k + Du_k + Fd_k \end{cases} \quad (2)$$

where $u_k = [u_{1k} \quad u_{2k}]^T$ is the input vector composed by the lean solvent flow rate u_1 and turbine extracted steam flow rate u_2, $y_k = [y_{1k} \quad y_{2k}]^T$ is the output vector composed by the CO_2 capture rate and reboiler temperature, d_k is the flue gas flow rate, x_k is the state vector; A, B, C, D, E, F are the local model matrices.

Equation (2) can be rewritten into an augmented form (3),

$$\begin{cases} x_{k+1} = Ax_k + \tilde{B}\tilde{u}_k \\ y_k = Cx_k + \tilde{D}\tilde{u}_k \end{cases} \quad (3)$$

where $\tilde{u}_k = [u_k^T \quad d_k^T]^T$ is the augmented input , and $\tilde{B} = [B \quad E]$, $\tilde{D} = [D \quad F]$ are the augmented system matrices. Since equation (3) is a typical state space type model, with the input, output and disturbance data being collected, conventional subspace identification approach can be directly used to identify the local system matrices.

To ensure that the generated data are suited for the local model identification, we keep all the control loops within the gCCS model closed except the CO_2 capture rate and reboiler temperature loops. The excitation signals for flue gas flow rate, lean solvent flow rate and turbine extracted steam flow rate are then designed and implemented on the gCCS model to achieve a persistent excitation of the system around the given CO_2 capture rate and reboiler temperature set-points. The corresponding data are then generated and collected for system identification.

The method of subspace identification is selected for the local model identification due to its following advantages:

a) it can identify the state-space model, which is suitable for advanced multi-variable control design directly from the input-output data;

b) the subspace identification is based on the computational tools such as orthogonal triangular decomposition and singular value decomposition (SVD), thus is computational efficient, and can avoid the problem of local minimum and convergence;

c) the system order can be easily selected during the identification procedure.

The detailed algorithm can be found in [47] and is not repeated here.

Remark 3.1 Different from the conventional MPC, the flue gas flow rate is considered in the prediction model (2) in the proposed method. Therefore, a more accurate prediction in the presence of flue gas flow rate variation can be made, and a quick rejection of this disturbance may be achieved by the developed MPC.

Remark 3.2 CO_2 concentration in the flue gas can be another factor which have significant impact on the PCC process. However, during the load change of coal-fired power plants, CO_2 concentration in flue gas only varies within a very small range (According to the design specification of a 1000MWe supercritical coal-fired power plant, CO_2 concentration in flue gas varies from 21.62wt% to 22.86wt% corresponding to power plant load changes from 50% to 100%, the variation is typically less than

1.5%). The reason is that the flue-gas oxygen content is strictly controlled by the power plant combustion system during the operation and meanwhile a suitable ratio between the amount of fuel and supplied air is always maintained to guarantee the efficiency of the combustion [48]. For this reason, CO_2 concentration variation is not considered in this study.

3.2.2 Local Predictive Control Design

Since the identification method is used for the local state-space model development, the derived state variables do not have physical meanings and thus cannot be measured. For this reason, build the following observer (4) to estimate the state x is necessary for the model prediction:

$$\begin{aligned} \hat{x}_{k+1} &= A\hat{x}_k + \tilde{B}\tilde{u}_k + K\left[\hat{y}(k) - y(k)\right] \\ \hat{y}(k) &= C\hat{x}_k + \tilde{D}\tilde{u}_k \end{aligned} \qquad (4)$$

in which the symbol "^" indicates the estimate. Following the method in Feng [49], the observer gain K can be calculated if there exist matrices H and G, and a symmetric positive definite matrix X, such that the following LMI problem is feasible:

$$\begin{bmatrix} H^T + H - X & (HA + GC)^T \\ HA + GC & X \end{bmatrix} > 0 \qquad (5)$$

and the observer gain $K = H^{-1}G$.

Then considering the following dynamic control objective function:

$$J = (\hat{y}_f - r_f)^T Q_f (\hat{y}_f - r_f) + \Delta u_f^T R_f \Delta u_f \qquad (6)$$

where $\hat{y}_f = \begin{bmatrix} \hat{y}_{k+1}^T & \hat{y}_{k+2}^T & \cdots & \hat{y}_{k+N_y}^T \end{bmatrix}^T$ is the prediction of future output within the predictive horizon N_y, it can be expressed by the future augmented input sequence $\tilde{u}_f = \begin{bmatrix} \tilde{u}_{k+1}^T & \tilde{u}_{k+2}^T & \cdots & \tilde{u}_{k+N_u}^T \end{bmatrix}^T$ for a control horizon N_u, by stacking up the predictive model (3) according to the current augmented input $\tilde{u}_k$, output y_k and estimated state $\hat{x}_k$:

$$\hat{y}_f = \psi_x \hat{x}_k + \psi_u \begin{pmatrix} \tilde{u}_k \\ \tilde{u}_f \end{pmatrix} + \psi_y y_k \qquad (7)$$

in which,

$$\psi_x = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{N_y-1} \end{bmatrix}(A + KC), \quad \psi_y = -\begin{bmatrix} C \\ CA \\ \vdots \\ CA^{N_y-1} \end{bmatrix}K,$$

$$\psi_u = \begin{bmatrix} C(B+KD) & D & 0 & \cdots & 0 \\ CA(B+KD) & CB & D & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{N_u-1}(B+KD) & CA^{N_u-2}B & \cdots & CB & D \\ CA^{N_u}(B+KD) & CA^{N_u-1}B & \cdots & CAB & CB + D \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ CA^{N_y-1}(B+KD) & CA^{N_y-2}B & \cdots & CA^{N_y-N_u}B & \sum_{j=0}^{N_y-N_u-1} CA^jB + D \end{bmatrix};$$

$r_f = \begin{bmatrix} r_{k+1}^T & r_{k+2}^T & \cdots & r_{k+N_y}^T \end{bmatrix}^T$ is the desired output set-points; Δu_f is the increment of future control input sequence $u_f = \begin{bmatrix} u_{k+1}^T & u_{k+2}^T & \cdots & u_{k+N_u}^T \end{bmatrix}^T$,which can be expressed by:

$$\Delta u_f = \psi \begin{bmatrix} u_k \\ u_f \end{bmatrix} \tag{8}$$

$$\psi = \begin{bmatrix} -I_2 & I_2 & 0 & \cdots & 0 \\ \cdots & -I_2 & I_2 & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & \cdots & -I_2 & I_2 \end{bmatrix}$$

in which, I_2 stands for a 2×2 identity matrices. $Q_f = I_{N_f} \otimes Q_0, R_f = I_{N_u} \otimes R_0$ are the weighting matrices of output and input, respectively.

Substitute equations (7) and (8) into the objective function (6), and at each sampling time, the optimal future control sequence u_f can be calculated by minimizing (6) subject to the input magnitude and rate constraints (9) and (10),

$$\begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} u_{min} \le u_f \le \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} u_{max} \tag{9}$$

$$\begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{min} \le \psi \begin{bmatrix} u_k \\ u_f \end{bmatrix} \le \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{max} \tag{10}$$

and the first element in u_f, u_{k+1} can be obtained as the optimal local control action.

Remark 3.3 Note that only the current flue gas flow rate value d_k can be measured at time instant k, and its future values d_{k+1}, d_{k+2},...,d_{k+Nu} are unknown to the system. Therefore, we assumed that the future values of flue gas flow rate are fixed as d_k over the control horizon N_u in this work, which brings the optimal control sequence into a suboptimal one. If future flue gas flow rate can be estimated correctly by the power plant, the information can be used to further improve the control performance.

3.2.3 Integral Action for Offset Free Tracking

In spite of the effectiveness of advanced identification methods, the model mismatch is unavoidable, therefore it is necessary to include the integral action into the predictive controller so that an offset-free tracking of the desired set-points can be attained.

To add the integral action, an incremental form of augmented model (3) is used for model prediction [46]. Following the same procedure, the future output can be predicted by:

$$\hat{y}_f = \mathbf{y}_k + \zeta \Delta \hat{y}_f \tag{11}$$

where $\mathbf{y}_k = \begin{bmatrix} y_k^T & y_k^T & \cdots & y_k^T \end{bmatrix}^T$, $\zeta = \begin{bmatrix} I_2 & 0 & \cdots & 0 \\ I_2 & I_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I_2 & I_2 & \cdots & I_2 \end{bmatrix}$, and $\Delta\hat{y}_f = \psi_x \Delta\hat{x}_k + \psi_u \begin{pmatrix} \Delta\tilde{u}_k \\ \Delta\tilde{u}_f \end{pmatrix} + \psi_y \Delta y_k$.

The input magnitude and rate constraints are changed to

$$\begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} (u_{min} - u_k) \le \zeta \Delta u_f \le \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} (u_{max} - u_k) \qquad (12)$$

$$\begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{min} \le \Delta u_f \le \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{max} \qquad (13)$$

At each sampling time, substitute equation (11) into the objective function (6), the optimal future incremental control sequence Δu_f can be calculated by minimizing (6) subject to the input magnitude and rate constraints (12) and (13). The value of $u_{k+1} = u_k + \Delta u_{k+1}$ can then be obtained as the optimal local control action.

3.2.4 Fuzzy Membership function design

With the three local predictive controllers being developed, a three rule fuzzy membership function $\omega_i(y_{1k})$ is designed as shown in Fig. 6 to connect them smoothly together and build the integrated MMPC system for the PCC process.

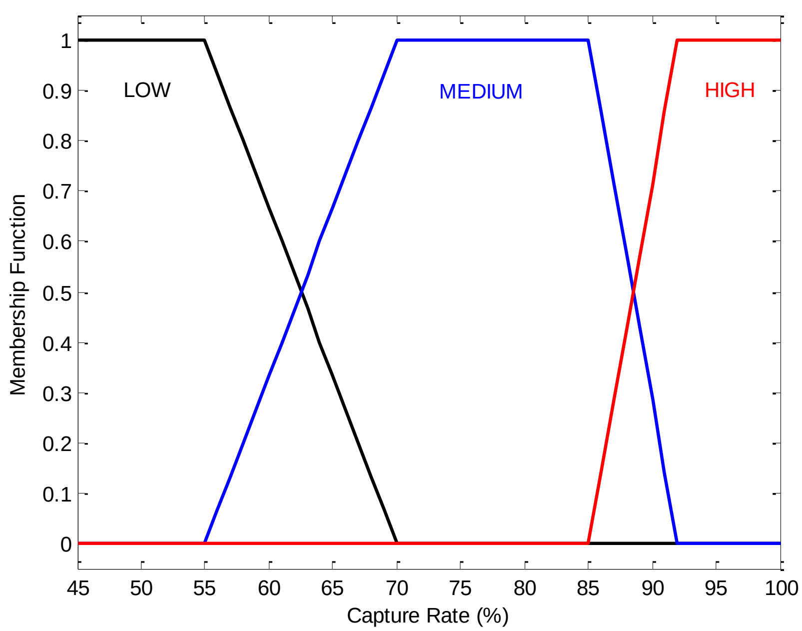

Fig. 6 Fuzzy membership functions of the MMPC system

CO_2 capture rate is selected as the scheduling variable and according to its current value y_{1k}, the fuzzy membership function value for the three local predictive controllers $\omega_i(y_{1k})$, i=1, 2, 3 can be obtained. The global optimal control action

$$u_{k+1} = \sum_{i=1}^{3} \omega_i (y_{1k}) u_{k+1}^{i} \qquad (14)$$

can be calculated at each sampling time and implemented on the PCC system to achieve a wide range flexible control (u_{k+1}^{i} is the optimal control action calculated by local predictive controller-i).

Remark 3.4 The objective of this paper is to design an MMPC for the PCC process to improve its flexible operation performance. Therefore, the main content of this paper is focused on the control layer (i.e. how to track the CO_2 capture rate set point quickly in a wide range and effectively handle the influences of flue gas flowrate variation) , not the scheduling and optimization layer. The set-points are assumed to be given already and dynamic tracking performance (6) is considered as the objective function. How to develop an economic MPC which directly consider the operating cost in the objective function instead of the dynamic control objectives will be our future interest.

IV. Simulation Results

This section demonstrates the MMPC controller design for the PCC process. The proposed controller is tested and compared with conventional PI controller and other types of predictive controllers. The sampling time of all the controllers is set as T_s=30s and for the MPCs, we set predictive horizon N_y=1200s, control horizon N_u=150s; the weighting matrices are set as Q_0=diag(40, 2); R_0=100×diag(1, 0.75) for a best CO_2 capture rate tracking control. The following input constraints are considered: $u_{min} = [0 \quad 0]^T, u_{max} = [1 \quad 0.075]^T$; $\Delta u_{min} = [-0.007 \quad -0.001]^T, \Delta u_{max} = [0.007 \quad 0.001]^T$ due to the physical limitations of the valves and pumps. In all the simulations, the controllers are implemented in MATLAB environment, it is communicated with the gCCS model through gOMATLAB interface at each sampling time.

The first case is designed to show the performance of predictive controllers over the PI controller. A small CO_2 capture rate change is considered: at t = 900 s the set-points of CO_2 capture rate changes from 80% to 70% at the ramping rate of 0.1%/30s and changes to 75% at t = 6900 s at the same ramping rate. The reboiler temperature set point is fixed at 383K.

Three controllers are used for comparison:

(1) MMPC using the integral action (MMPC_I);

(2) MMPC without using the integral action (MMPC);

(3) PI controllers (the parameters are tuned using the MATLAB PID Tuner toolbox at 80% capture rate operating point).

The simulation results in Figs. 7 and 8 show that the predictive controllers have the best performance, which can track the desired CO_2 capture rate quickly and closely during the simulation while maintaining the reboiler temperature well around 383K. The MPCs advantages in multi-variable, large inertial and constrained system control are clearly shown through this simulation. For the PI controller, although its parameters are already well tuned, due to its error based regulating mechanism and SISO loop design approach, the tracking speed is much slower compared with the MPCs, which cannot attain a satisfactory control performance for the complex PCC process. We can also find from Fig. 7 that, without using the integral action, there exists small control offset for the MMPC because the modeling mismatches are unavoidable.

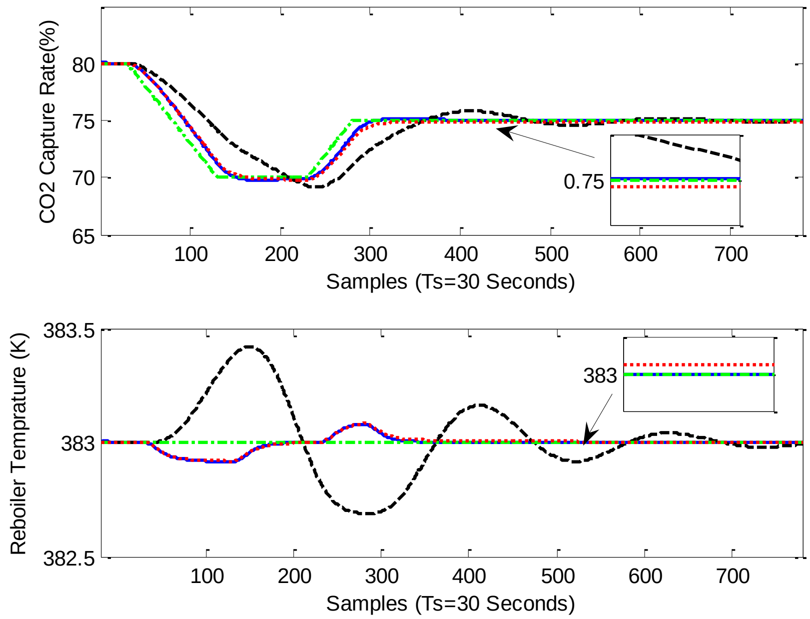

Fig. 7 Performance of the PCC system for a 80%-70%-75% CO_2 capture rate change: output variables (solid in blue: MMPC_I; dotted in red: MMPC; dashed in black: PI; dot-dashed in green: reference)

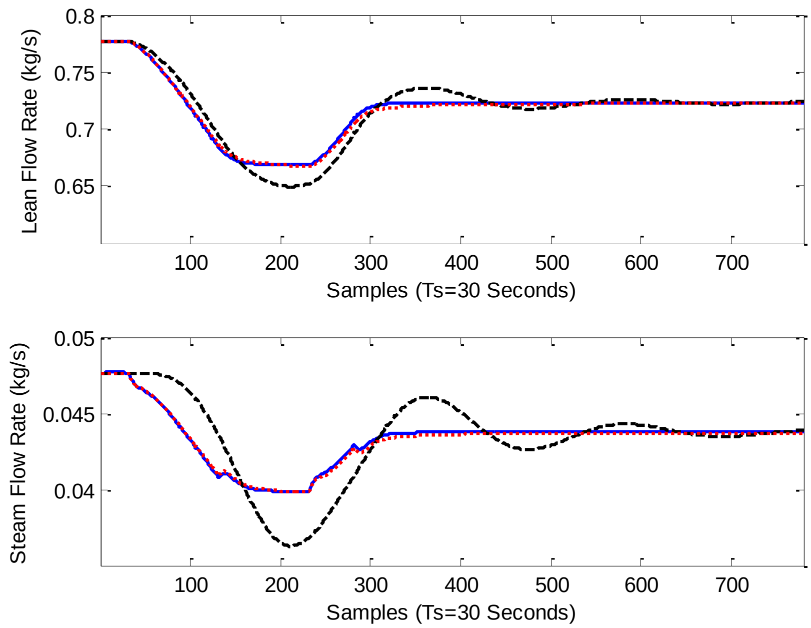

Fig. 8 Performance of the PCC system for a 80%-70%-75% CO_2 capture rate change: manipulated variables (solid in blue: MMPC_I; dotted in red: MMPC; dashed in black: PI)

Then we designed the second and third cases to test the effectiveness for the multi-model predictive controllers for wide range operating point change. In Case 2, we suppose that at t=900s, the set-point of CO_2 capture rate decreases from 80% to 45% at the ramping rate of 0.14%/30s and the reboiler temperature set point is fixed at 383K. Two predictive controllers without using the integral action are used for comparison:

(1) Multi-model predictive controller without using the integral action (MMPC);

(2) Linear model predictive controller without using the integral action (linear-MPC), (predictive model is identified around 80% capture rate operating point).

The simulation results are shown in Figs. 9 and 10.

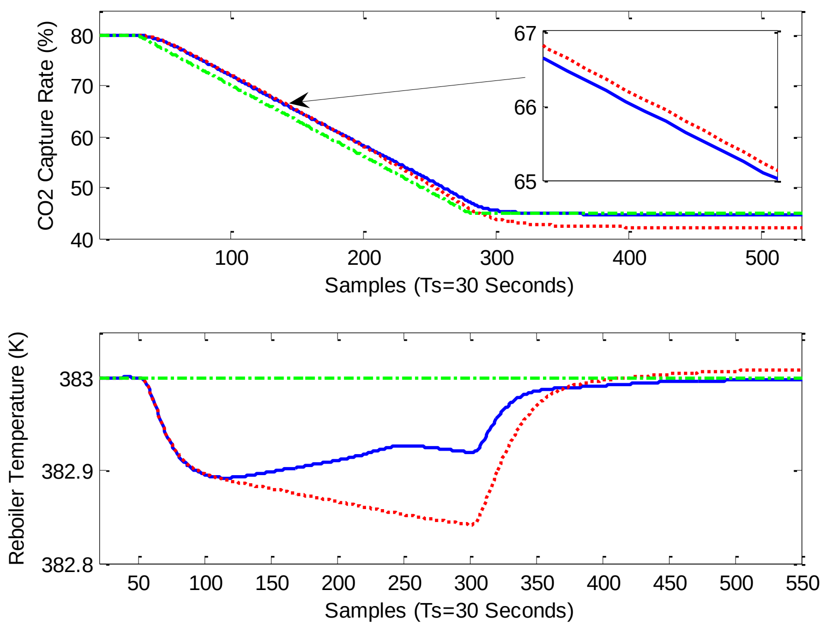

Fig. 9 Performance of the PCC system for a 80%-45% wide range CO_2 capture rate change: output variables (solid in blue: MMPC; dotted in red: linear-MPC; dot-dashed in green: reference)

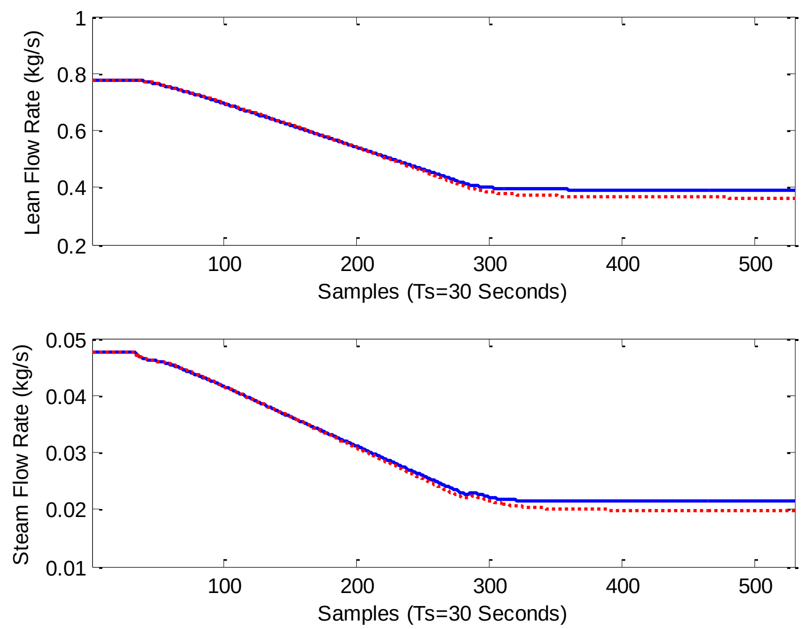

Fig. 10 Performance of the PCC system for a 80%-45% wide range CO_2 capture rate change: manipulated variables (solid in blue: MMPC; dotted in red: linear-MPC)

The results show that, around 80% capture rate operating point where the linear MPC is developed, both MPCs have almost the same performance, which can control the PCC system satisfactory. However, as the operating point deviates away from 80% point, the modeling mismatch of linear-MPC becomes bigger and thus the control performance is degraded. At 45% operating point, significant control offset can be viewed from Fig. 9 for the linear-MPC. On the other hand for the MMPC, because a combination of several linear MPCs is used, better model prediction can be made during the whole operating range change, therefore faster CO2 capture rate tracking and better reboiler temperature regulating can be achieved by the MMPC, the control offset at 45% operating point is also much smaller compared with the linear-MPC.

Then another wide range operating point variation is considered in Case 3. We suppose that at t=900s the set-point of capture rate changes from 80% to 95% at the ramping rate of 0.15%/30s and changes to 50% at t=6900s at the same ramping rate. The reboiler temperature set point is fixed at 383K. Two predictive controllers using the integral action are used for comparison:

(1) Multi-model predictive controller using the integral action (MMPC_I);

(2) Linear model predictive controller using the integral action (linear-MPC_I), (predictive model is identified around 70% capture rate operating point).

The simulation results are shown in Figs. 11 and 12.

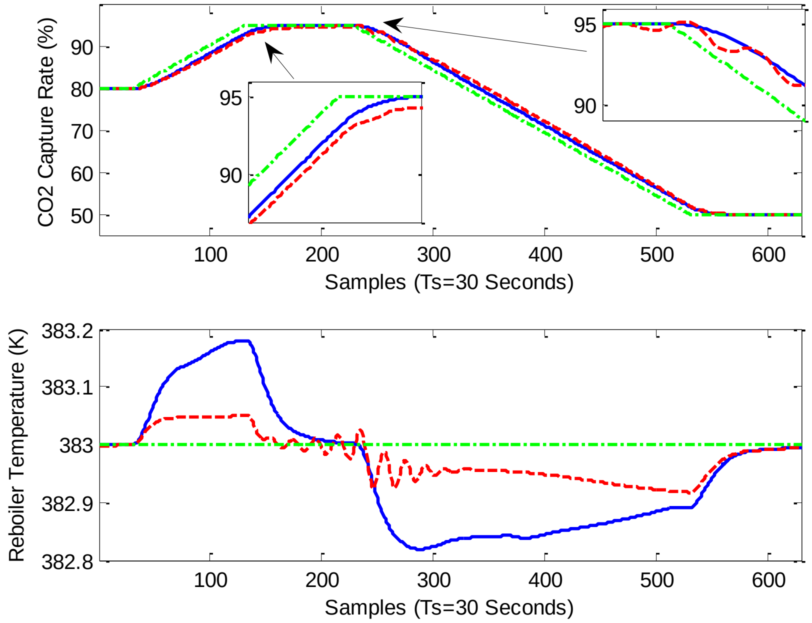

Fig. 11 Performance of the PCC system for a 80%-95%-50% wide range CO_2 capture rate change: output variables (solid in blue: MMPC_I; dotted in red: linear-MPC_I; dot-dashed in green: reference)

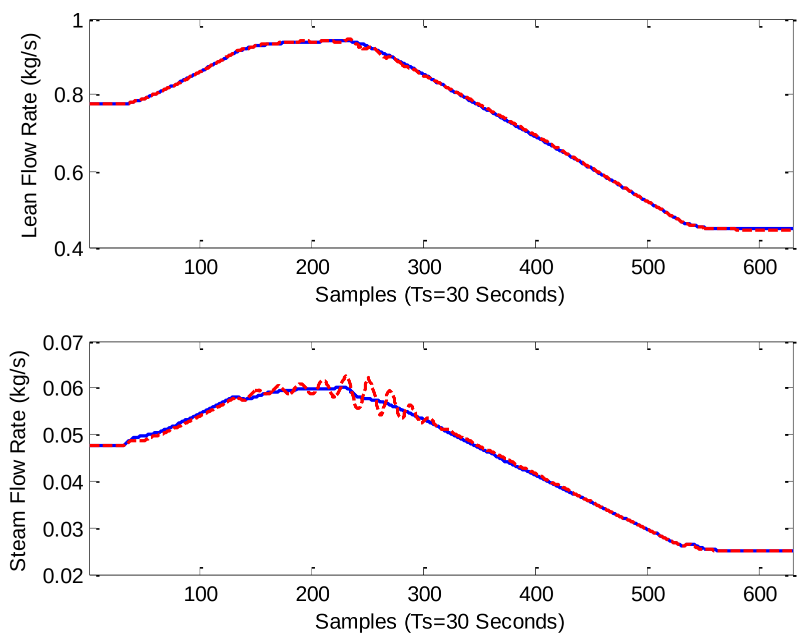

Fig. 12 Performance of the PCC system for a 80%-95%-50% wide range CO_2 capture rate change: manipulated variables (solid in blue: MMPC_I; dotted in red: linear-MPC_I)

The results show that, in order to better respond to the wide range CO_2 capture rate change, when the capture rate rise/ drop demand is given, the MMPC_I quickly increases/ decreases the extracted flow rate. Although a bigger reboiler temperature rise/drop can be viewed in Fig. 11, this action can change the CO_2 loading in lean flow more effectively and is helpful for achieving a rapid capture rate control performance, which is the primary objective of the control system. The results also show that a severe performance degradation and system unstable is occurred for the linear-MPC_I around the 95% capture rate operating point. The reason is that, the nonlinearity of the system is extremely strong around 95% operating point, the resulting significant modeling mismatch exceeds the preconfigured robustness bound of the linear-MPC_I.

Cases 2 and 3 clearly demonstrate the proposed MMPC strategy in the condition of wide range CO_2 capture rate change. Then we devise the last simulation to show the effectiveness of the proposed controller in the presence of power plant flue gas flow rate change. We suppose that, the system is operating at 80% capture rate point, and at t=1500s and t=4500s, the power plant changes its loading condition, resulting in a flue gas flow rate change from 0.13kg/s to 0.1235kg/s and to 0.15kg/s as shown in the upper figure of Fig. 13. Three controllers are used for comparison:

(1) Multi-model predictive controller without using the integral action (MMPC);

(2) Multi-model predictive controller without using the integral action and without using the flue gas disturbance model (MMPC_2);

(3) PI controllers (the parameters are tuned using the MATLAB PID Tuner toolbox at 80% capture rate operating point).

The simulation results are shown in Figs. 13 and 14.

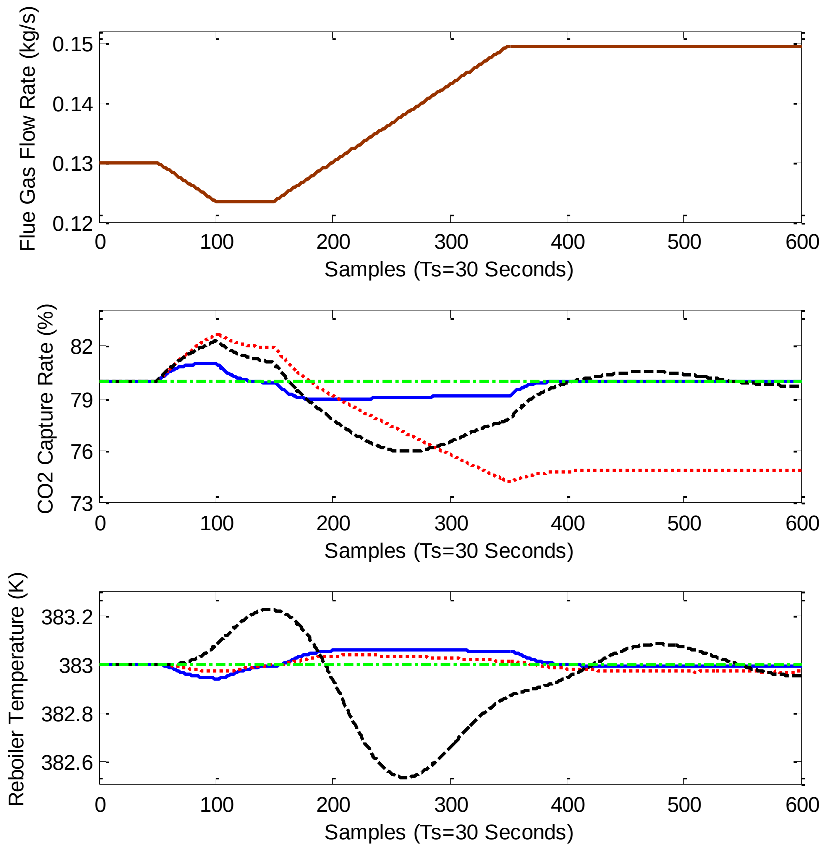

Fig. 13 Performance of the PCC system in the presence of power plant flue gas variation: output variables (solid in blue: MMPC; dotted in red: MMPC_2; dashed in black: PI; dot-dashed in green: reference)

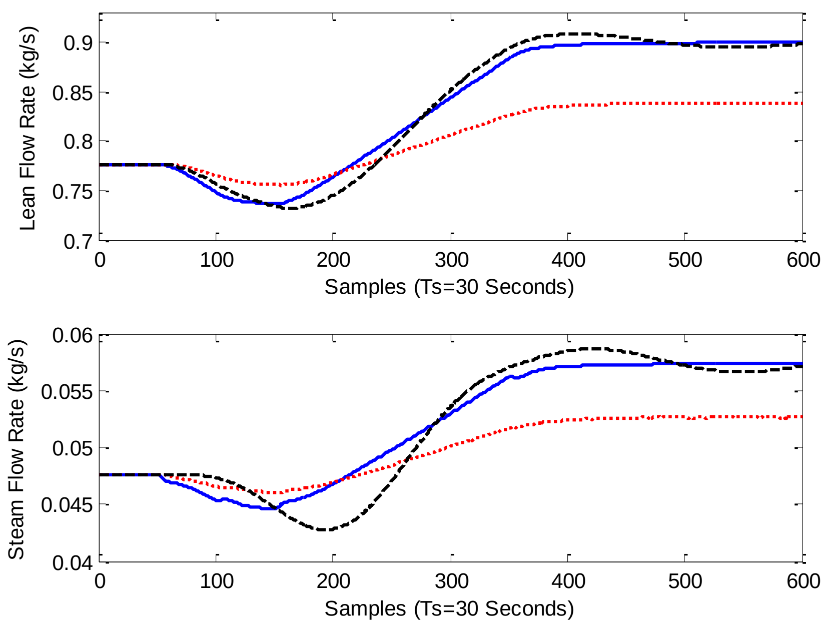

Fig. 14 Performance of the PCC system in the presence of power plant flue gas variation: manipulated variables (solid in blue:

MMPC; dotted in red: MMPC_2; dashed in black: PI)

The results show that the proposed MMPC can effectively handle the flue gas variation and keeps the PCC plant operating in an expected condition. On the other hand, without using the flue gas disturbance model, a big prediction error is produced by the MMPC_2 in the case of flue gas variation, therefore, its control performance is degraded severely and a huge control offset is occurred. The dynamic performance of PI controller is also worse than the proposed MMPC, which needs a much longer regulation time to bring the far deviated capture rate and reboiler temperature back to their set points. However, by using the integral action, an offset-free control can be attained by the PI finally.

It should be emphasized that, the use of multiple models instead of one can be viewed as an approach to reduce the modeling mismatches of the single linear model in the case of wide range CO_2 capture rate change. Besides this, two other techniques are used in the proposed MMPC design to further alleviate the impact of uncertainty:

1) For measured uncertainty: the flue gas flow rate is considered in the MMPC design stage, so that the model mismatches or uncertainties caused by flue gas flow rate variation can be effectively dealt with; 2) For unmeasured uncertainty: integral action is taken into account in the MMPC design to guarantee an offset-free control performance.

Nevertheless, if the plant variations or other disturbances are too strong and exceed the pre-configured robustness bound of the MMPC, severe degradation of control performance will still be encountered. In that case, online update of the model may be necessary for the MMPC system.

V. CONCLUSION

To achieve a wide range flexible operation of the post combustion CO_2 capture process, a novel multi-model predictive control system is developed in this paper using the combination of several local linear predictive controllers. Nonlinearity of the solvent-based capture system along the operating range is firstly investigated to provide a guidance for the local model/controller selection and connection. Subspace identification method is then used to build the state space local models around the selected operating point, and predictive controllers are designed based on these models. To improve the adaption ability of the capture system to the power plant load variation, the flue gas flow rate of power plant is considered as an additional measured disturbance in the local model identification, so that an accurate prediction can be made by the developed model in the presence of flue gas flow rate variation. Combined together by a fuzzy membership function, the resulting multi-model predictive control system can attain a rapid change of the CO_2 capture rate in a wide range and reject the power plant flue gas disturbance effectively. The advantages of the proposed multi-model predictive controller design are demonstrated through the simulations on an MEA-based CO_2 capture process developed on gCCS platform.

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REFERENCES

[1] IPCC. Special report on carbon dioxide capture and storage . Cambridge, UK: Cambridge University Press, 2005.

[2] IPCC. Climate change 2007: synthesis report. Contribution of working groups I, II and III to the fourth assessment report of the intergovernmental panel on climate change (pp. 30–37). Geneva, Switzerland, 2007.

[3] IEA. Energy Technology Perspectives 2008. IEA/OECD, Paris, France, 2008.

[4] A. Lawal, M. Wang, P. Stephenson and O. Obi, "Demonstrating full-scale post-combustion CO_2 capture for coal-fired power plants through dynamic modelling and simulation,"Fuel, vol. 101, pp. 115-128, 2012.

[5] A. Lawal, M. Wang, P. Stephenson, G. Koumpouras and H. Yeung "Dynamic modelling and analysis of post-combustion CO_2 chemical absorption process for coal-fired power plants," Fuel, vol. 89, pp. 2791-2801, 2010.

[6] J. Oexmann. Post-Combustion CO_2 Capture: Energetic Evaluation of chemical Absorption Processes in Coal-Fired Steam Power Plants. Ph.D. thesis, Technische Universitat Hamburg-Harburg, 2011.

[7] J. Oexmann, C.Hensel, A.Kather. Post-combustion CO_2-capture from coal-fired power plants: preliminary evaluation of an integrated chemical absorption process with piperazine-promoted potassium carbonate. International Journal of Greenhouse Gas Control, vol. 2, pp. 539–552, 2008.

[8] P. Mores and et al. CO_2 capture in power plants: Minimization of the investment and operating cost of the post-combustion process using MEA aqueous solution. International Journal of Greenhouse Gas Control, vol. 10, pp. 148–163, 2012.

[9] A. Raksajati, M. T. Ho and D. E. Wiley. Reducing the cost of CO_2 capture from flue gases using aqueous chemical absorption. Ind. Eng. Chem. Res, vol. 52, no. 47, pp. 16887-16901, Nov 2013.

[10] M. Karimi, H. F. Svendsen and M. Hillestad. Capital costs and energy considerations of different alternative stripper configurations for post combustion CO_2 capture. Chemical Engineering Research and Design, vol. 89, no. 8, pp. 1229–1236, 2011.

[11] L. Duan, M. Zhao and Y. Yang. Integration and optimization study on the coal-fired power plant with CO_2 capture using MEA. Energy, vol. 45, pp.107-116, 2012.

[12] Q. Chen, C. Kang, Q. Xia and et al. Optimal flexible operation of a CO_2 capture power plant in a combined energy and carbon emission market. IEEE Trans. Power Syst., vol. 27, no. 3, pp.1602-1608, Aug. 2012.

[13] A. Arce, N. Mac Dowell, N. Shah and L.F. Vega, " Flexible operation of solvent regeneration systems for CO_2 capture processes using advanced control techniques: Towards operational cost minimisation," International Journal of Greenhouse Gas Control, vol. 11, pp. 236-250, 2012.

[14] N. A. Manaf, A. Qadir and A. Abbas, The hybrid MPC-MINLP algorithm for optimal operation of coal-fired power plants with solvent based post-combustion CO2capture, Petroleum, vol. 3, pp. 155-166, 2017.

[15] Y. Lin, T. Pan, D. Wong and et al. Plantwide control of CO_2 capture by absorption and stripping using monoethanolamine solution. 2011 American Control Conference, San Francisco, CA, USA, Jun 29-Jul 1, 2011.

[16] Y. Lin, D. Wong, S. Jang and et al, Control strategies for flexible operation of power plant with CO_2 capture plant, AICHE Journal, vol. 58, no. 9, pp. 2697-2704, 2012.

[17] A. Cormos, M. Vasile and M. Cristea, Flexible operation of CO_2 capture processes integrated with power plant using advanced control techniques，12th International Symposium on Process Systems Engineering and 25th European Symposium on Computer Aided Process Engineering, Copenhagen, Denmark, May 31-Jun 4, 2015.

[18] Z. He, M. H. Sahraei, L. A. Recardez-Sandoval, Flexible operation and simultaneous scheduling and control of a CO_2 capture plant using model predictive control, International Journal of Greenhouse Gas Control, vol. 48, pp. 300-311, 2016.

[19] M. Bui, I. Gunawan, V. Verheyen and et al, Flexible operation of CSIRO's post-combustion CO2capture pilot plant at the AGL Loy Yang power station, International Journal of Greenhouse Gas Control, vol. 48, pp. 188-203, 2016.

[20] M. Zaman, H. Jang, M. Rizman and et al, Optimal design for flexible operation of the post-combustion CO_2 capture plant with uncertain economic factors, Computers and Chemical Engineering,vol. 84, pp. 199-207, 2016.

[21] X. Luo and M. Wang, Optimal operation of MEA-based post-combustion carbon capture for natural gas combined cycle power plants under different market conditions, International Journal of Greenhouse Gas Control, vol. 48, pp. 312-320, 2016.

[22] X. Wu, J. Shen, Y. Li, and K. Y. Lee, Steam power plant configuration, design and control, WIREs Energy Environ, vol. 4, no. 6, pp. 537-563, Nov-Dec. 2015.

[23] T. Nittaya, P. L. Douglas, E. Croiset and et al. Dynamic modelling and control of MEA absorption processes for CO_2 capture from power plants. Fuel, vol. 116, pp. 672-691,2014.

[24] M. Schach, R. Schneider, H. Schramm and et al. Control structure design for CO_2-absorption processes with large operating ranges. Energy Technology. vol.1, no. 4, pp. 233-244, Apr 2013.

[25] M. Panahi, S. Skogestad, Economically efficient operation of CO_2 capturing process part I: self-optimizing procedure for selecting the best controlled variables, Chemical Engineering and Processing: Process Intensification, vol. 50, no.3, pp. 247-253, 2011.

[26] M. Panahi, S. Skogestad, Economically efficient operation of CO_2 capturing process part II: Design of control layer, Chemical Engineering and Processing: Process Intensification, vol. 52, pp. 112-124, 2012.

[27] J. B. Rawlings, Tutorial overview of model predictive control. IEEE Control Systems Magazine, vol. 20(3), pp. 38–52, 2000.

[28] A. Bedelbayev, T. Greer and B. Lie. Model based control of absorption tower for CO_2 capturing. 49th Scandinavian Conference on Simulation and Modeling, Oct 2008.

[29] E. D. Mehleri, N. Mac Dowell and N. F. Thornhill, Model Predictive Control of Post-Combustion CO_2 Capture Process integrated with a power plant，12th International Symposium on Process Systems Engineering and 25th European Symposium on Computer Aided Process Engineering, Copenhagen, Denmark, May 31-Jun 4, 2015.

[30] Q. Zhang, R. Turton and D. Bhattacharyya, Development of Model and Model-Predictive Control of an MEA-Based Post-combustion CO_2 Capture Process, Industrial & Engineering Chemistry Research, vol. 55, no. 5, pp. 1292-1308, 2016.

[31] J. Åkesson, C.D. Laird, G. Lavedan and et al, Nonlinear Model Predictive Control of a CO_2 Post-Combustion Absorption Unit, Chemical Engineering & Technology, vol. 35, no. 3, pp. 445-454, 2012.

[32] K. Prölß, H. Tummescheit, S. Velut and et al, Dynamic model of a post-combustion absorption unit for use in a non-linear model predictive control scheme, Energy Procedia, vol. 4, 2620-2627, 2011.
[33] M. H. Sahraei, L. A. Ricardez-Sandoval, Controllability and optimal scheduling of a CO_2 capture plant using model predictive control, International Journal of Greenhouse Gas Control, vol. 30, pp. 58-71, 2014.
[34] M. T. Luu, N. A. Manaf and A. Abbas, Dynamic modelling and control strategies for flexible operation of amine-based post-combustion CO2capture systems, International Journal of Greenhouse gas Control, vol. 39, pp. 377-389, 2015.
[35] A. Lawal, M. Wang, P. Stephenson and et al, Dynamic modelling of CO_2 absorption for post combustion capture in coal-fired power plants, Fuel, vol. 88, pp. 2455-2462, 2009.
[36] S. Ziaii, G.T. Rochelle and T. F. Edgar, Dynamic modeling to minimize energy use for CO_2 capture in power plants by aqueous monoethanolamine, Ind. Eng. Chem. Res, vol. 48, no. 13, pp. 6105-6111, 2009.
[37] K. Dietl, A. Joos and G. Schmitz, Dynamic analysis of the absorption/desorption loop of a carbon capture plant using an object-oriented approach, Chemical Engineering and Processing: Process Intensification, vol. 52, pp.132-139, 2012
[38] S. A. Jayarathna, B. Lie, M. C. Melaaen, Amine based CO_2 capture plant: dynamic modeling and simulations. International Journal of Greenhouse Gas Control, vol. 14, pp. 282-290. 2013,
[39] J. Rodriguez, A. Andrade, A. Lawal and et al, An integrated framework for the dynamic modelling of solvent-based CO_2 capture processes, Energy Procedia vol.63, pp. 1206-1217, 2014.
[40] E. Mechleri, A. Lawal, A. Ramos and et al, Process control strategies for flexible operation of post-combustion CO_2 capture plants, International Journal of Greenhouse Gas Control, vol. 57, pp. 14-25, 2017.
[41] P. Mores, N. Rodríguez, N. Scenna and et al, CO_2 capture in power plants: Minimization of the investment and operating cost of the post-combustion process using MEA aqueous solution, International Journal of Greenhouse Gas Control, vol. 10, pp. 148-163, 2012.
[42] P. Mores, N. Scenna and S, Mussati, CO_2 capture using monoethanolamine (MEA) aqueous solution: modeling and optimization of the solvent regeneration and CO_2 desorption process. Energy, vol. 45, no.1, pp. 1042-1058, 2012,
[43] F. Li, J. Zhang, E. Oko and et al, Modelling of a post-combustion CO_2 capture process using neural networks, Fuel, vol. 151, pp. 156-163, 2015.
[44] N. A. Manaf, A. Cousins, P. Feron and et al, Dynamic modelling, identification and preliminary control analysis of an amine-based post-combustion CO_2 capture pilot plant, Journal of Cleaner Production, vol. 113, pp. 635-653, 2016.
[45] B. Anderson, T. Brinsmead, F. Bruyne, J. Hespanha, D. Liberzon, and A. Morse, Multi model adaptive control. Part 1: Finite controller coverings, Int. J. Robust Nonlinear Control, vol. 10, pp. 909–929, 2000.
[46] X. Wu, J. Shen, Y. Li, and K. Y. Lee, Data-driven modeling and predictive control for boiler-turbine unit. IEEE Transactions on Energy Conversion, vol. 28, no.3, pp. 470–81, 2013.
[47] S. Qin, An overview of subspace identification, Comput Chem Eng, vol. 30, pp, 1502-1513, 2006.
[48] D. Lindsey, Power-Plant Control and Instrumentation: The Control of Boilers and HRSG Systems. Stevenage, UK: IEE Press; 2000.
[49] G. Feng, A survey on analysis and design of model-based fuzzy control systems. IEEE Transactions on Fuzzy Systems, vol. 14, no. 5, pp. 676-697, 2006.